The Student/Teacher Achievement Ratio (STAR) Project

Jay Bendre, 920211348

01-16-2022

Abstract

Using the data gathered in The Student/Teacher Achievement Ratio (STAR), we explore the application of a two-way ANOVA model in quantifying the effectiveness of the program in improving the overall grades for students in the first grade. The main aim is to get insights into the dataset and try and figure out how well did reducing the class sizes help in improving the grades of the students involved.

Introduction

The current world is extremely competitive with a sense of competition felt by students in grades as early as their second or third grade. Almost all kindergarten students nowadays have to go through more academic instruction as opposed to creative routes like music and art, engulfing most of their time in attending to academic worksheets. From a study conducted in 2016 by the University of Virginia, about 62% of the 2700 teachers surveyed thought that the students needed to know the alphabet before enrolling to the kindergarten [1].

Institutions have been trying various methods to find methods in improving the efficacy of their education system and getting an overall higher performing class - to assure a better chance of success in the industry later on. One of such studies was conducted from 1985 - 1989 by the State department of Education backed by the Tennessee General Assembly [2]. The main aim of this study was to check whether having a smaller class size is effective in improving the overall grades of the students in kindergarten and continued through third grade. By going through with this study, it would help in understanding the effectiveness of the one to one attention and a smaller class size and its correlation in improvement of the grades. The STAR study also analyzes the long term effects of this in the Lasting Benefits Study (LBS) [3] by considering a sub-sample of the students considered in the project STAR. In this study we try to answer 2 of the following questions:

1. Do people in classes with small sizes have any effect in the math scores of students in 1st grade?
2. Does the average score of a particular class type have a higher mean than the others?

To answer the above questions, we follow the structure mentioned here: First, we conduct exploratory data analysis in order to verify assumptions that need to be met to conduct the required ANOVA analysis. Next we fit a 2-way ANOVA model to study the effect of students in the first grade by subsetting the entire dataset. We then shift gears by checking the statistical significance of all the results obtained from the model by hypothesis testing. We conduct tests to check for equal variances and normality. Later we conduct Tukey Test to check whether the mean of a particular class type is greater than all others.

Background

The dataset to be studied is imported using the AER library. It consists of the public access dataset used in the STAR project and consists of many demographic variables and variables describing the teachers qualifications and the math scores obtained in various class types. Over 7000 students in 79 schools were randomly assigned to one of the following three interventions: small class (13-17 Students), regular class (22-25 Students) and regular-with-aide class (22-25 students with a full-time teacher's aide). The following table below describes all the variables important to the study.

Table 1: Important variables used in the study

Variable Names	Variable Type	Variable Description
math1	Quantitative	Total scaled math scores - also the Response variable
school1	Indicator	Indicator for the region of school
schoolid1	Quantitative	Unique identifier for the school
lunch1	Indicator	Indicator for whether school offers free lunch
star1	Indicator	Indicator for all types of classes Regular, Regular+aide and Small

Descriptive analysis

```r
# Preview of the dataset
STAR %>% head(5)
```

Getting a preview into the dataset

```
##      gender ethnicity   birth        stark star1        star2        star3
## 1122 female      afam 1979 Q3         <NA>  <NA>         <NA>      regular
## 1137 female      cauc 1980 Q1        small small        small        small
## 1143 female      afam 1979 Q4        small small regular+aide regular+aide
## 1160   male      cauc 1979 Q4         <NA>  <NA>         <NA>        small
## 1183   male      afam 1980 Q1 regular+aide  <NA>         <NA>         <NA>
##      readk read1 read2 read3 mathk math1 math2 math3   lunchk lunch1   lunch2
## 1122    NA    NA    NA   580    NA    NA    NA   564     <NA>   <NA>     <NA>
## 1137   447   507   568   587   473   538   579   593 non-free   free non-free
## 1143   450   579   588   644   536   592   579   639 non-free   <NA> non-free
## 1160    NA    NA    NA   686    NA    NA    NA   667     <NA>   <NA>     <NA>
## 1183   439    NA    NA    NA   463    NA    NA    NA     free   <NA>     <NA>
##        lunch3    schoolk  school1  school2  school3  degreek  degree1  degree2
## 1122     free       <NA>     <NA>     <NA> suburban     <NA>     <NA>     <NA>
## 1137     free      rural    rural    rural    rural bachelor bachelor bachelor
## 1143 non-free   suburban suburban suburban suburban bachelor   master bachelor
## 1160 non-free       <NA>     <NA>     <NA>    rural     <NA>     <NA>     <NA>
## 1183     <NA> inner-city     <NA>     <NA>     <NA> bachelor     <NA>     <NA>
##       degree3   ladderk   ladder1    ladder2    ladder3 experiencek experience1
## 1122 bachelor      <NA>      <NA>       <NA>     level1          NA          NA
## 1137 bachelor    level1    level1 apprentice apprentice           7           7
## 1143 bachelor    level1 probation     level1     level1          21          32
## 1160 bachelor      <NA>      <NA>       <NA>     level1          NA          NA
## 1183     <NA> probation      <NA>       <NA>       <NA>           0          NA
```

```
##      experience2 experience3 tethnicityk tethnicity1 tethnicity2 tethnicity3
## 1122          NA          30        <NA>        <NA>        <NA>        cauc
## 1137           3           1        cauc        cauc        cauc        cauc
## 1143           4           4        cauc        afam        afam        cauc
## 1160          NA          10        <NA>        <NA>        <NA>        cauc
## 1183          NA          NA        cauc        <NA>        <NA>        <NA>
##      systemk system1 system2 system3 schoolidk schoolid1 schoolid2 schoolid3
## 1122    <NA>    <NA>    <NA>      22      <NA>      <NA>      <NA>        54
## 1137      30      30      30      30        63        63        63        63
## 1143      11      11      11      11        20        20        20        20
## 1160    <NA>    <NA>    <NA>       6      <NA>      <NA>      <NA>         8
## 1183      11    <NA>    <NA>    <NA>        19      <NA>      <NA>      <NA>
```

```
# Looking at all the columns
colnames(STAR)
```

```
##  [1] "gender"      "ethnicity"   "birth"       "stark"       "star1"
##  [6] "star2"       "star3"       "readk"       "read1"       "read2"
## [11] "read3"       "mathk"       "math1"       "math2"       "math3"
## [16] "lunchk"      "lunch1"      "lunch2"      "lunch3"      "schoolk"
## [21] "school1"     "school2"     "school3"     "degreek"     "degree1"
## [26] "degree2"     "degree3"     "ladderk"     "ladder1"     "ladder2"
## [31] "ladder3"     "experiencek" "experience1" "experience2" "experience3"
## [36] "tethnicityk" "tethnicity1" "tethnicity2" "tethnicity3" "systemk"
## [41] "system1"     "system2"     "system3"     "schoolidk"   "schoolid1"
## [46] "schoolid2"   "schoolid3"
```

```
# List of columns possibly relevant to analyzing only grade 1 math scores

new_colnames <- c("gender","ethnicity","star1","read1","math1","lunch1","school1","degree1","ladder1","e

# Creating new dataset with all variables related to grade 1
df <- STAR %>% select(all_of(new_colnames))

df %>% head(5)
```

```
##      gender ethnicity star1 read1 math1 lunch1  school1  degree1   ladder1
## 1122 female      afam  <NA>    NA    NA   <NA>     <NA>     <NA>      <NA>
## 1137 female      cauc small   507   538   free    rural bachelor    level1
## 1143 female      afam small   579   592   <NA> suburban   master probation
## 1160   male      cauc  <NA>    NA    NA   <NA>     <NA>     <NA>      <NA>
## 1183   male      afam  <NA>    NA    NA   <NA>     <NA>     <NA>      <NA>
##      experience1 tethnicity1 system1 schoolid1
## 1122          NA        <NA>    <NA>      <NA>
## 1137           7        cauc      30        63
## 1143          32        afam      11        20
## 1160          NA        <NA>    <NA>      <NA>
## 1183          NA        <NA>    <NA>      <NA>
```

Looking at missing values We know that missing values in star1 just implies that they didnt attend any STAR classes

Also there is no point in looking at rows were the total scaled math scores are 0 so the point is to get rid of all the rows in the **'math1'** column and check for

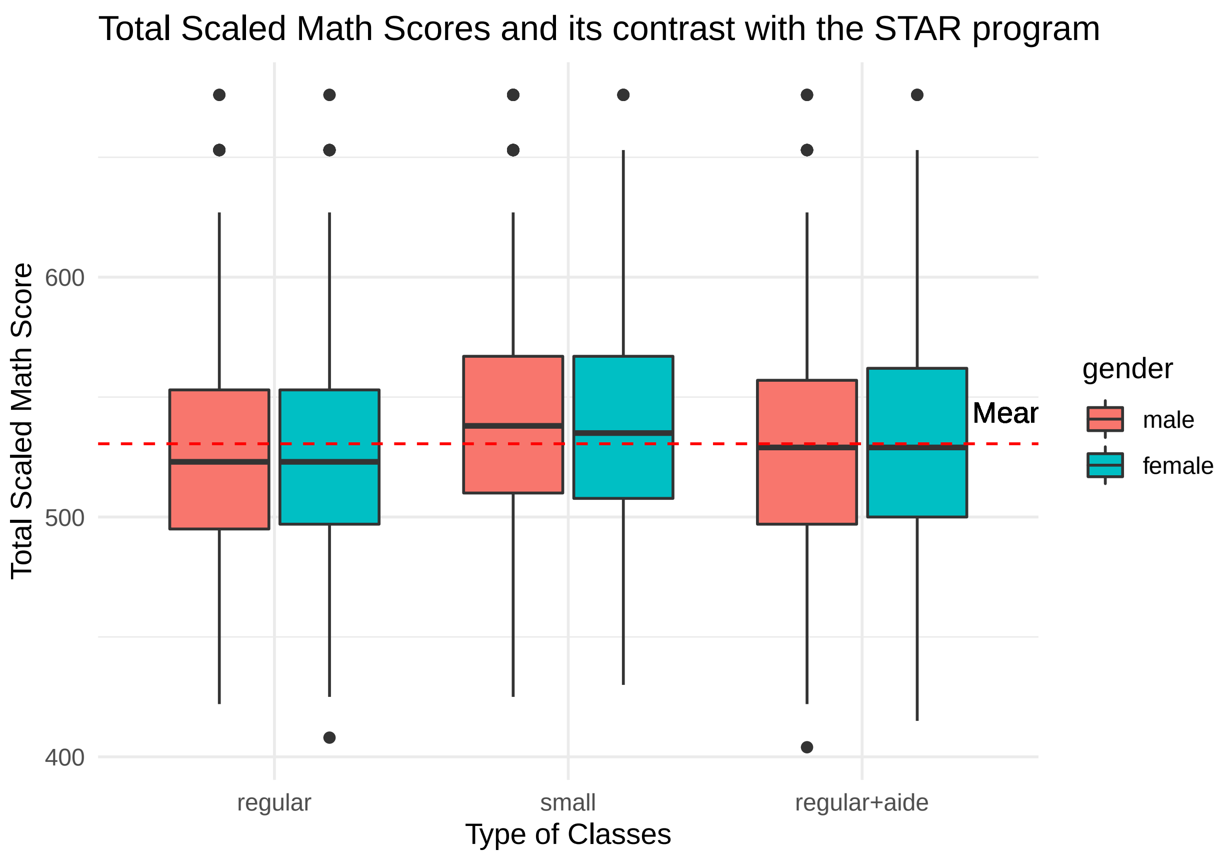
```r
df <- df %>% filter(!is.na(math1))

describe(df)
```

```
##               vars    n   mean    sd median trimmed   mad min max range  skew
## gender*          1 6600   1.48  0.50      1    1.48  0.00   1   2     1  0.07
## ethnicity*       2 6598   1.35  0.53      1    1.29  0.00   1   6     5  2.01
## star1*           3 6600   1.96  0.85      2    1.95  1.48   1   3     2  0.08
## read1            4 6379 520.86 55.17    514  517.54 57.82 404 651   247  0.48
## math1            5 6600 530.53 43.10    529  529.42 43.00 404 676   272  0.29
## lunch1*          6 6437   1.51  0.50      2    1.51  0.00   1   2     1 -0.04
## school1*         7 6600   2.45  0.91      3    2.45  1.48   1   4     3 -0.30
## degree1*         8 6588   1.36  0.51      1    1.31  0.00   1   4     3  1.09
## ladder1*         9 6567   2.18  1.78      1    1.89  0.00   1   6     5  1.04
## experience1     10 6588  11.63  8.92     10   10.61  8.90   0  42    42  0.94
## tethnicity1*    11 6558   1.17  0.38      1    1.09  0.00   1   2     1  1.72
## system1*        12 6600  19.05 11.02     17   18.46  8.90   1  42    41  0.47
## schoolid1*      13 6600  41.00 22.74     41   41.20 28.17   1  80    79 -0.06
##               kurtosis   se
## gender*          -2.00 0.01
## ethnicity*       10.25 0.01
## star1*           -1.60 0.01
## read1            -0.43 0.69
## math1             0.04 0.53
## lunch1*          -2.00 0.01
## school1*         -0.88 0.01
## degree1*          0.97 0.01
## ladder1*         -0.56 0.02
## experience1       0.56 0.11
## tethnicity1*      0.97 0.00
## system1*         -0.92 0.14
## schoolid1*       -1.19 0.28
```

Visualization of data to gain more insights into data

1. Looking at average mean scores based on the star variable

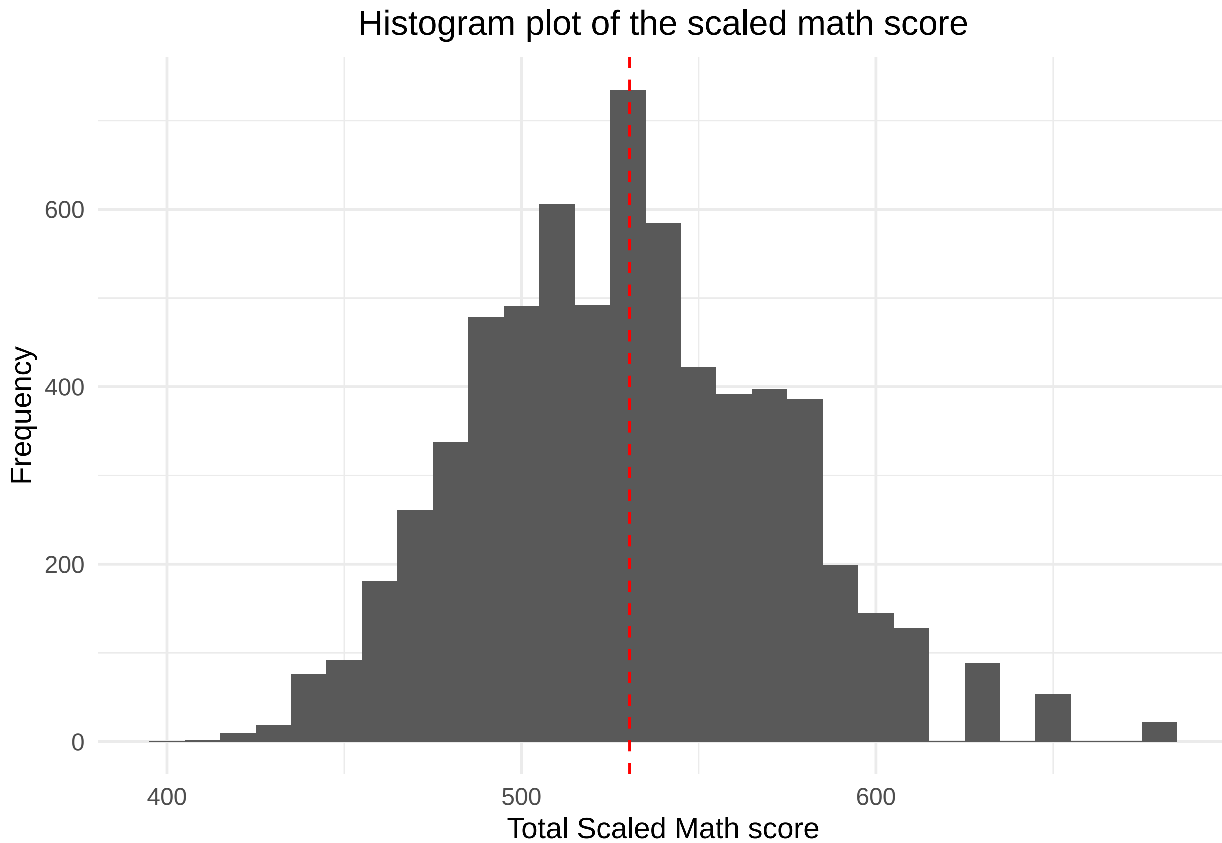
```r
ggplot(df, aes(x = star1, y = math1, fill = gender)) + geom_boxplot() + xlab("Type of Classes") + ylab(
```



Looking at the above plot we can see that there is no significant difference in the mean between male and female students. In contrast to the population mean ie total mean across all types of classes, the average mean of **small** class size is higher than all other class types ie. regular and regular with aide. Furthermore it can be seen that the classes with aide ie. full time professor available for aide perform better than regular classes.

2. Since **math1** is supposed to be the response variable for the model its important to see if the response variable is following a normal distribution which we do using a histogram.

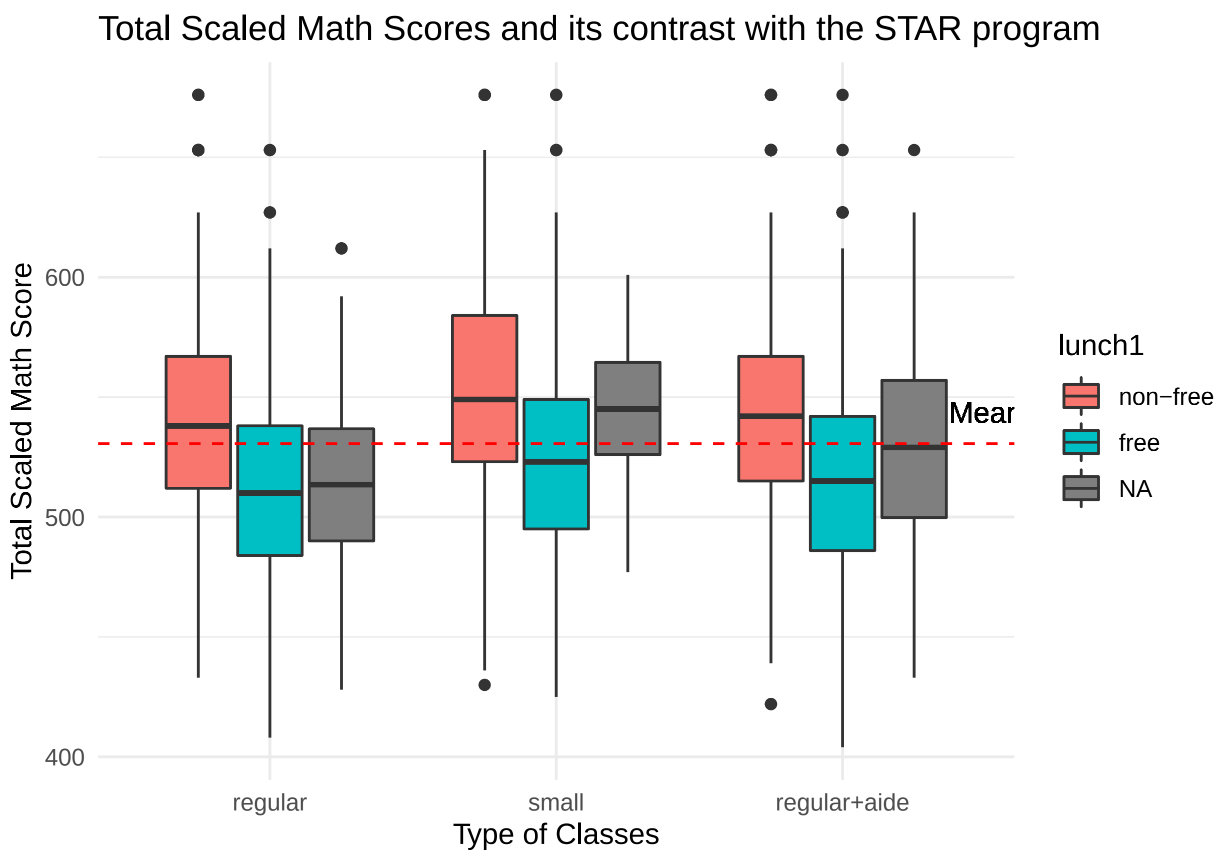
```
ggplot(df, aes(x = math1)) + geom_histogram(binwidth = 10) + xlab("Total Scaled Math score") + ylab("Fr
```



We can see that there is some semblance of normality that the response variable in the currenty study seems to follow. But in order to confirm whether any transformations are required, we could run it through a boxcox transformation and confirm our suspicion of whether the response truly requires any sort of transformation or not.

3. We can check whether the incentive of a free lunch is enough for increasing the average grades of the students based on the type of class

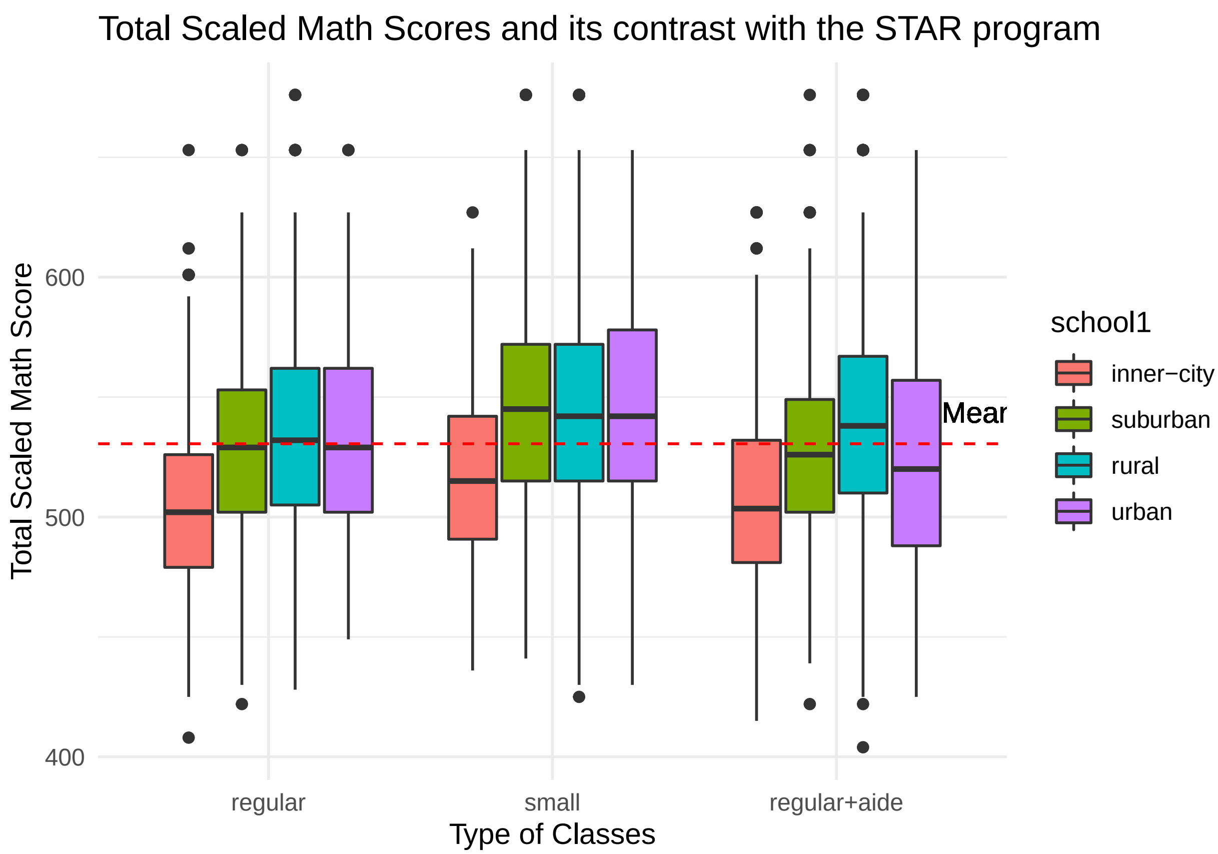
```
ggplot(df, aes(x = star1, y = math1, fill = lunch1)) + geom_boxplot() + xlab("Type of Classes") + ylab(
```



There doesnt seem to be any effect of the incentive of getting a free lunch and the hypothesis of it resulting in higher scores. Infact we can see that, when offered a free lunch, the mean scores are significantly lesser than the non free lunch.

4. Looking at the scores based on every school currently in the dataset.

```
ggplot(df, aes(x = star1, y = math1, fill = school1)) + geom_boxplot() + xlab("Type of Classes") + ylab
```



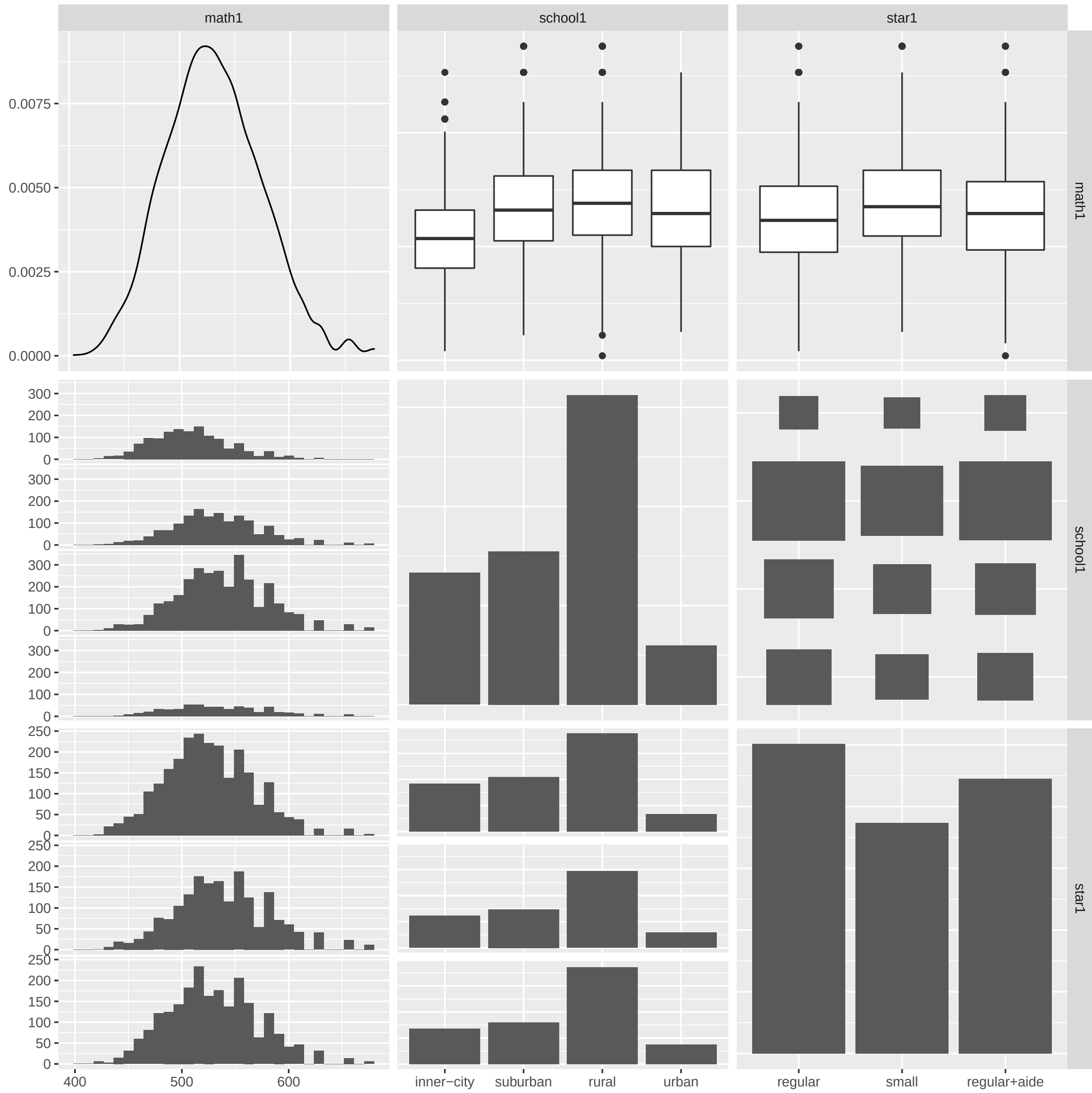
There necessarily isnt a distinctive rule that could be observed from the above plot. We can see that in general regardless of the type of class its been part of, the average scores are lower in the schools located in the inner-city as opposed to schools belonging to other areas. However among the other 3 regions ie. suburban, rural and urban we dont see a consistent pattern across all 3 class types.

5. Looking at pairwise relationships between variables

Since the study only involves knowing about the school indicator and star indicator the plot would only be talking about the scaled math scores and the above two indicators.

```
ggpairs(df %>% select(c("math1","school1","star1")))
```

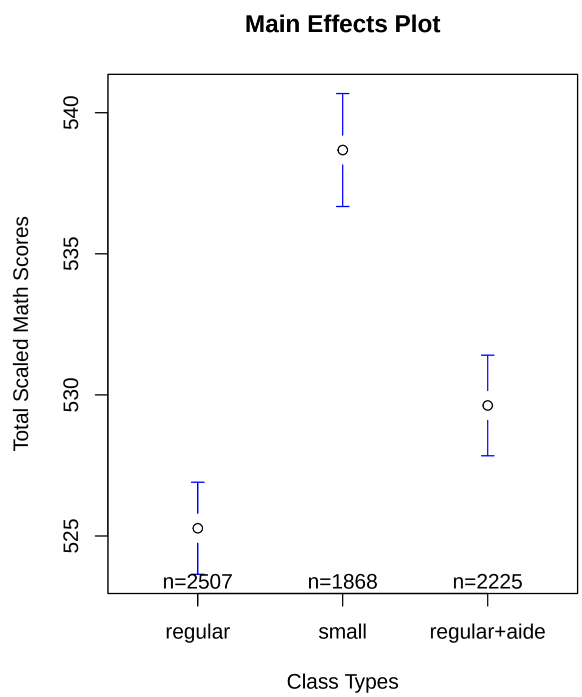
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

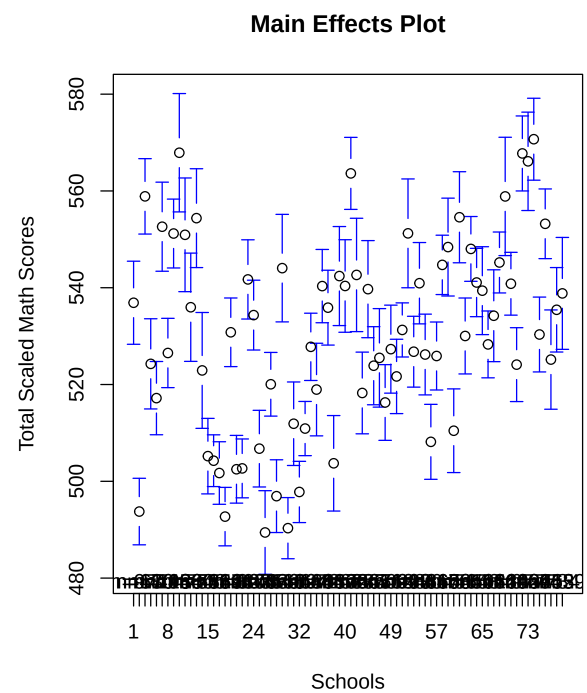


From the above plot we can observe that the study involves more number of schools belonging in the rural regions as opposed to in the other regions. We can also see that the response variable **math1** follows normal distribution across all types of schools and across all types of classes, making it suitable for analysis.

6. Looking at the main effects plot to see the difference in the means between any class size.

```
par(mfrow = c(1,2))
plotmeans(math1 ~ star1, xlab = "Class Types", ylab = "Total Scaled Math Scores", data = df, main = "Mai
plotmeans(math1 ~ schoolid1, xlab = "Schools", ylab = "Total Scaled Math Scores", data = df, main = "Mai
```





We can see that the mean of the students in the small class type is significantly higher than the other two class types, which could be indicative of small class size's effectiveness in improving the performance of the students involved in the STAR projects initiative.

Inferential analysis

To conduct analysis, the best option to understand the effects of the indicators 'schoolid1' and 'star1' is to fit a 2-way ANOVA model. T he two-way analysis of variance (ANOVA) is an extension of the one-way ANOVA that examines the influence of two different categorical independent variables on one continuous dependent variable. The two-way ANOVA not only aims at assessing the main effect of each independent variable but also if there is any interaction between them [4]. A 2 way anova model is given as the following:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \epsilon_{jk}$$

where,

1. i represents the class type

- $i = 1$: small class type
- $i = 2$: regular class type
- $i = 3$: regular + aide class type

2. j represents the school ids

3. k represents the number of observations in the dataset.

4. Y_{ijk} represents the total scaled math scores.

5. $\alpha_i = \mu - \mu_i$ represents the difference in population mean - sample mean of a particular class type.
6. $\beta_i = \mu - \mu_i$ represents the difference in population mean - sample mean of different schools.
7. ϵ_{ijk} represents the error.

Fitting the Model We use the aov() function to fit the above suggested model.

```
model <- aov(math1 ~ star1 + schoolid1, data = df)
summary(model)
```

```
##                 Df  Sum Sq Mean Sq F value Pr(>F)    
## star1            2  195075   97538   67.37 <2e-16 ***
## schoolid1       75 2622986   34973   24.16 <2e-16 ***
## Residuals     6522 9442537    1448                   
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

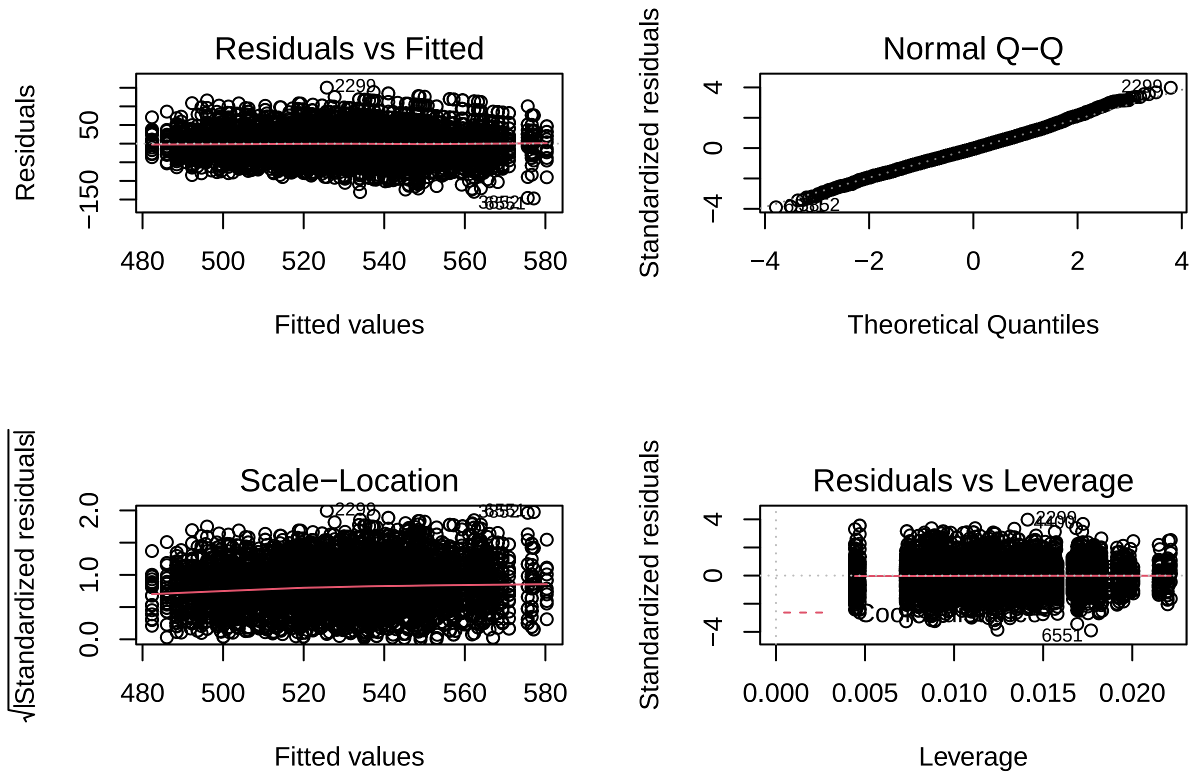
From the above ANOVA model we can see that the P-value is significant at significance level $\alpha = 0.05$.

To note that due to the large number of schoolids it would not be feasible to report all the possible coefficients for schoolids.

Sensitivity analysis

In sensitivity analysis, we can check for the model diagnostics by looking at a few diagnostic plots. These help in understanding attributes regarding the residuals of the model and whether they violate the model assumptions. Lets look at the plots.

```
par(mfrow = c(2,2))
plot(model)
```



Following can be seen from the above plots:

- Looking at the $Residuals$ v/s $FittedValues$ we can see that the overall variance seems to be constant throughout. The strip-like distribution is just the effect of indicator variables which causes data points to stack up on a particular factor value. This makes it important to check whether the variances remain the same across all the levels of the factors which is handled later in the study using Levene's Test [6].
- Next the QQ-plot suggests that the residuals follow a normal distribution. There doesnt seem to be any visible skew in the data. We later check this using the Shapiro - Wilk and Kolmogorov - Smirnov Test.

One of the model assumptions is to check whether the residuals terms are normally distributed. The residuals are generally the error in the actual and predicted value of the response variable (in this case the total scaled math scores). These residuals need to be normally distributed so that we can make accurate inferences from the model. Lets check for the normality of the residuals using the Shapiro Wilke Test [5].

In a Shapiro Wilk Test, the null hypothesis H_0 states that the population to be tested follows a normal distribution meanwhile the alternate hypothesis H_a states that the population doesnt comply with the normal distribution and could be any other distribution. However, since the sample size is greater than 5000, R doesnt allow to conduct a Shapiro Wilk Test. The alternative to that is Kolmogorov-Smirnov Test which has the same setup as the Shapiro-Wilk Test.

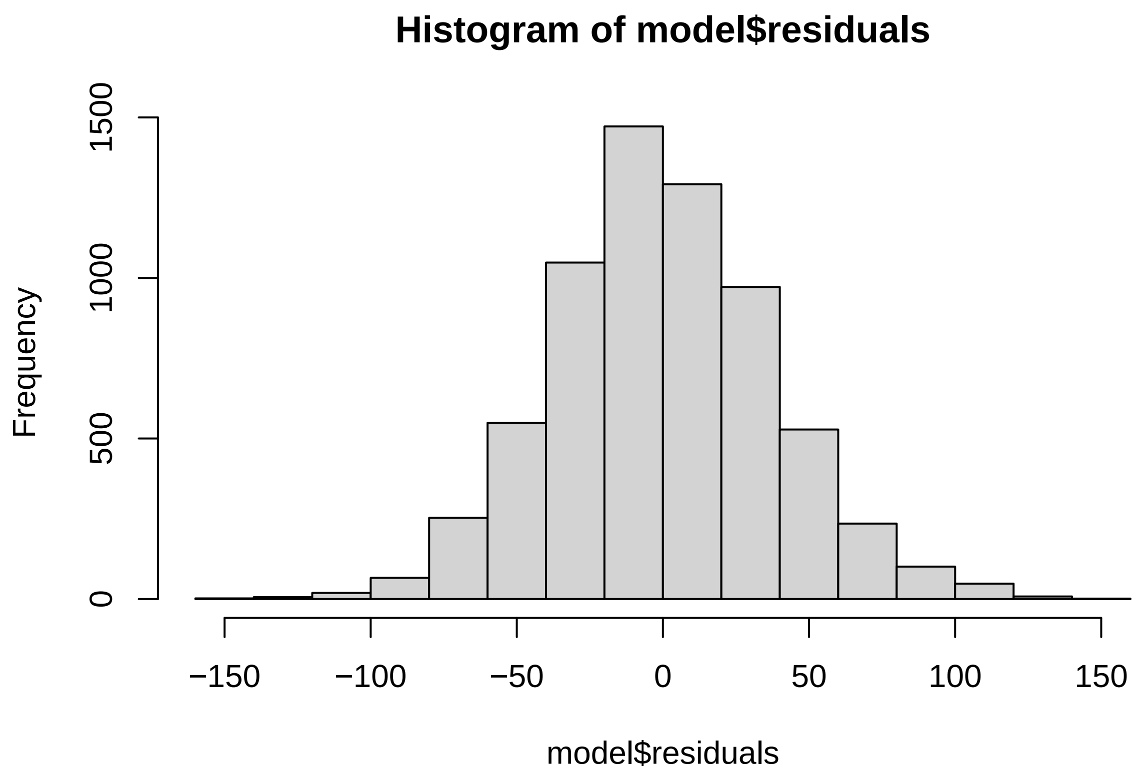
```
ks.test(model$residuals,'pnorm')
```

```
##
##  One-sample Kolmogorov-Smirnov test
```

```
##
## data:  model$residuals
## D = 0.48115, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

Since the p-value is significant at $\alpha = 0.05$ we can conclude that the residuals follow normal distribution. Lets look at the distribution of the residuals.

```
hist(model$residuals)
```



From the above plot we can see that the residuals seem to be normally distributed. Hence the results that can be inferred from the model can be interpretted to be accurately reported.

Next, to check for equal variances among the groups we need to check using the levennes test [6]. We assume that samples from all the groups are independent while conducting the Levene's Test. The null hypothesis H_0 states that there is no difference in the variances across all the groups ie. $\sigma_1 = \sigma_2 = ... = \sigma_n$ for n groups. The alternate hypothesis H_a states that none of the variances are the same. If the P-value is less than α we can reject H_0. Assuming $\alpha = 0.05$ lets conduct the Levene's Test.

```
leveneTest(math1 ~ star1 * schoolid1, data = df)
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##         Df F value    Pr(>F)
## group  223  2.2331 < 2.2e-16 ***
##       6376
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Since the p-value in the test is less than α we can conclude that the variances across all groups are not equal. It could be due to uneven distribution of the data points across all groups and also contribution of the variables effect on the scaled scores.

Now coming to answering the questions first we need to check if the means across all groups remains the same or not using a F-test.

Null Hypothesis $H_0 : \mu_{small} = \mu_{regular} = \mu_{regular+aide}$

Alternate Hypothesis H_a : Not all μ_i are the same.

Let significance level $= \alpha = 0.05$

The testing condition in this case is defined as: We can reject the null hypothesis if at given significance level α ,

$$F^* > F(1-\alpha, r-1, n_T - r)$$

In the given problem, $r = 3$ and $n_T = 6600$

We conduct a F-test to check for the above hypothesis. The F statistic is defined as:

$$F^* = \frac{MSTR}{MSE} = \frac{\frac{SSTR}{r-1}}{\frac{SSE}{n_T - r}}$$

Lets have a quick look at the ANOVA table again,

```
summary(model)
```

```
##                Df  Sum Sq Mean Sq F value Pr(>F)
## star1           2  195075   97538   67.37 <2e-16 ***
## schoolid1      75 2622986   34973   24.16 <2e-16 ***
## Residuals    6522 9442537    1448
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

From the anova table we get the value of $F^* = \frac{97538}{1448} = 67.37$

The critical value of $F = 2.9970931$

Since the $F^* > F$ we can reject the null hypothesis that the means of all class types are same. This was also backed by the main effects plot we saw in the descriptive analysis section where we can see the mean of small class size being greater than others.

Now lets check if the mean of a specific group is more than the mean of others. In order to do so we use the Tukey test [7]. Tukey test is a single-step multiple comparison procedure and statistical test. It is a post-hoc analysis, what means that it is used in conjunction with an ANOVA.

It allows to find means of a factor that are significantly different from each other, comparing all possible pairs of means with a t-test like method.

```
TukeyHSD(aov(math1 ~ star1, data = df), conf.level = 0.95)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = math1 ~ star1, data = df)
```

```
##
## $star1
##                            diff         lwr        upr     p adj
## small-regular         13.403299  10.339053 16.467545 0.0000000
## regular+aide-regular   4.350737   1.430754  7.270720 0.0013965
## regular+aide-small    -9.052562 -12.198626 -5.906497 0.0000000
```

From the above result we can see that all the results are significant at $\alpha = 0.05$ as all the p-values are lower than alpha. By this we can conclude that the mean of class **small** is always greater than the remaining two classes ie. **regular** and **regular+aide** . We can also conclude that **regular+aide** has a higher mean than **regular**.

Discussion

To summarise what we saw in this study, we were able to successfully answer both the main questions. By fitting an anova model with the schoolids and the class types we got a model which indicated that both the variables are significant in the total scaled math scores. It makes sense that the school ids came as significant because the translation of that would be that depending on the school , the services provided and the environment at the school, the average score would differ. But the main takeaway is that a small class size will lead to larger average scores as opposed to other class types. This was compared and proven using a Tukey Test in the sensitivity analysis section. From this we can infer that due to a smaller class and the more 1:1 attention of the professor would lead to a better performing class as opposed to even a regular class with a constant aide being provided to class. However, the current model looks at every specific school id and that may lead to noise in the interpretation of the results. A better option would be to find a grouping metric for all the school ids maybe based on states or the funding being provided by the government and then study how effectively has the funding being used with the STAR programme and its correlation with the better performance of the class. Further, A look into the lasting effect of this in the future and potential career choices and whether having a small class at an older age would also have the same effect as it had on the lower grades. The LBS study conducted with the STAR project is something to dwell into and explore in the future and study the prolonged effects of the STAR programme.

Acknowledgement

All help received in the project was obtained from the teammates assigned in the roster, Professor Shihzhe Chen and the TA's of the course STA 207.

Reference

[1] Moyer, M. W. (2020, April 17). Early education is more demanding than ever, and experts have concerns. The New York Times. Retrieved January 20, 2022, from https://www.nytimes.com/2020/04/17/parenting/early-childhood-education-demands.html

[2] Imbens, G., & Rubin, D. (2015). Stratified Randomized Experiments. In Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction (pp. 187-218). Cambridge: Cambridge University Press. doi:10.1017/CBO9781139025751.010

[3] 92 - files.eric.ed.gov. (n.d.). Retrieved January 20, 2022, from https://files.eric.ed.gov/fulltext/ED354992.pdf

[4] Statistical Methods for Research II - github pages. (n.d.). Retrieved January 21, 2022, from https://chenshizhe.github.io/STA207W2020/

[5] Shapiro-Wilk Test. Shapiro-Wilk Test - an overview | ScienceDirect Topics. (n.d.). Retrieved January 21, 2022, from https://www.sciencedirect.com/topics/psychology/shapiro-wilk-test

[6] Levene's Test - Binghamton University. (n.d.). Retrieved January 21, 2022, from https://biotoolbox.binghamton.edu/Biostatistics/Biostatistics%20Student%20Tutorials/Levene%20Test/Levene.pdf

[7] 7.4.7.1. Tukey's method. (n.d.). Retrieved January 21, 2022, from https://www.itl.nist.gov/div898/handbook/prc/section4/prc471.htm

Session info

Report information of your `R` session for reproducibility.

```
sessionInfo()
```

```
## R version 4.1.1 (2021-08-10)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 22000)
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=English_India.1252  LC_CTYPE=English_India.1252
## [3] LC_MONETARY=English_India.1252 LC_NUMERIC=C
## [5] LC_TIME=English_India.1252
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] knitr_1.36      gplots_3.1.1    GGally_2.1.2    lindia_0.9
##  [5] ggplot2_3.3.5   psych_2.1.9     dplyr_1.0.7     AER_1.2-9
##  [9] survival_3.2-11 sandwich_3.0-1  lmtest_0.9-39   zoo_1.8-9
## [13] car_3.0-11      carData_3.0-4
##
## loaded via a namespace (and not attached):
##  [1] Rcpp_1.0.7         lattice_0.20-44    gtools_3.9.2       assertthat_0.2.1
##  [5] digest_0.6.27      utf8_1.2.2         plyr_1.8.6         R6_2.5.1
##  [9] cellranger_1.1.0   evaluate_0.14      highr_0.9          pillar_1.6.2
## [13] rlang_0.4.11       curl_4.3.2         readxl_1.3.1       data.table_1.14.0
## [17] Matrix_1.3-4       rmarkdown_2.11     labeling_0.4.2     splines_4.1.1
## [21] stringr_1.4.0      foreign_0.8-81     munsell_0.5.0      compiler_4.1.1
## [25] xfun_0.26          pkgconfig_2.0.3    mnormt_2.0.2       tmvnsim_1.0-2
## [29] htmltools_0.5.2    tidyselect_1.1.1   gridExtra_2.3      tibble_3.1.4
## [33] rio_0.5.27         reshape_0.8.8      fansi_0.5.0        crayon_1.4.1
## [37] withr_2.4.3        bitops_1.0-7       MASS_7.3-54        grid_4.1.1
## [41] nlme_3.1-152       gtable_0.3.0       lifecycle_1.0.0    DBI_1.1.1
## [45] magrittr_2.0.1     scales_1.1.1       KernSmooth_2.23-20 zip_2.2.0
## [49] stringi_1.7.4      farver_2.1.0       ellipsis_0.3.2     generics_0.1.0
## [53] vctrs_0.3.8        openxlsx_4.2.4     Formula_1.2-4      RColorBrewer_1.1-2
## [57] tools_4.1.1        forcats_0.5.1      glue_1.4.2         purrr_0.3.4
## [61] hms_1.1.0          abind_1.4-5        parallel_4.1.1     fastmap_1.1.0
## [65] yaml_2.2.1         colorspace_2.0-2   caTools_1.18.2     haven_2.4.3
```